Data Analysis and Visualisation with Python

Numerical Python (NumPy)

- NumPy is the most foundational package for numerical computing in Python.
- If you are going to work on data analysis or machine learning projects, then having a solid understanding of NumPy is nearly mandatory.
- Indeed, many other libraries, such as pandas and scikit-learn, use NumPy's array objects as the *lingua franca* for data exchange.
- One of the reasons as to why NumPy is so important for numerical computations is because it is designed for efficiency with large arrays of data. The reasons for this include:

    - It stores data internally in a continuous block of memory, independent of other in-built Python objects.

    - It performs complex computations on entire arrays without the need for for loops.

What you'll find in NumPy

- ndarray: an efficient multidimensional array providing fast array-orientated arithmetic operations and flexible *broadcasting* capabilities.
- Mathematical functions for fast operations on entire arrays of data without having to write loops.
- Tools for reading/writing array data to disk and working with memory-mapped files.
- Linear algebra, random number generation, and Fourier transform capabilities.
- A C API for connecting NumPy with libraries written in C, C++, and FORTRAN. This is why Python is the language of choice for wrapping legacy codebases.

The NumPy ndarray: A multi-dimensional array object

- The NumPy ndarray object is a fast and flexible container for large data sets in Python.
- NumPy arrays are a bit like Python lists, but are still a very different beast at the same time.
- Arrays enable you to store multiple items of the same data type. It is the facilities around the array object that makes NumPy so convenient for performing math and data manipulations.

Ndarray vs. lists

- By now, you are familiar with Python lists and how incredibly useful they are.
- So, you may be asking yourself:

  "I can store numbers and other objects in a Python list and do all sorts of computations and manipulations through list comprehensions, for-loops etc. What do I need a NumPy array for?"

- There are very significant advantages of using NumPy arrays overs lists.

Creating a NumPy array

- To understand these advantages, lets create an array.
- One of the most common, of the many, ways to create a NumPy array is to create one from a list by passing it to the `np.array()` function.

In:
```
import numpy as np
list1 = [0, 1, 2, 3, 4]
arr = np.array(list1)

print(type(arr))
print(arr)
```

Out:
```
In [1]: runfile('C:/Users,
wdir='C:/Users/Lew_laptop,
<type 'numpy.ndarray'>
[0 1 2 3 4]
```

Differences between lists and ndarrays

- The key difference between an array and a list is that arrays are designed to handle vectorised operations while a python lists are not.
- That means, if you apply a function, it is performed on every item in the array, rather than on the whole array object.

- Let's suppose you want to add the number 2 to every item in the list. The intuitive way to do this is something like this:

In:
```
import numpy as np
list1 = [0, 1, 2, 3, 4]
list1 = list1+2
```

Out:
```
File "C:/Users/Lew_laptop/.spyder-py3/temp.py", line 9, i
  list1 = list1+2

TypeError: can only concatenate list (not "int") to list
```

- That was not possible with a list, but you can do that on an array:

In:
```
import numpy as np
list1 = [0, 1, 2, 3, 4]
arr = np.array(list1)
print(arr)
arr = arr+2
print(arr)
```

Out:
```
In [7]: runfile('C:/Users
Lew_laptop/.spyder-py3')
[0 1 2 3 4]
[2 3 4 5 6]
```

- It should be noted here that, once a Numpy array is created, you cannot increase its size.
- To do so, you will have to create a new array.

Create a 2d array from a list of list

- You can pass a list of lists to create a matrix-like a 2d array.

In:
```
import numpy as np
list2 = [[0, 1, 2], [3, 4, 5], [6, 7, 8]]
arr2=np.array(list2)
print(arr2)
```

Out:
```
[[0 1 2]
 [3 4 5]
 [6 7 8]]
```

The dtype argument

- You can specify the data-type by setting the dtype() argument.
- Some of the most commonly used NumPy dtypes are: float, int, bool, str, and object.

In:
```
import numpy as np
list2 = [[0, 1, 2], [3, 4, 5], [6, 7, 8]]
arr3=np.array(list2, dtype='float')
print(arr3)
```

Out:
```
[[0. 1. 2.]
 [3. 4. 5.]
 [6. 7. 8.]]
```

The astype argument

- You can also convert it to a different data-type using the astype method.

In:
```
import numpy as np
list2 = [[0, 1, 2], [3, 4, 5], [6, 7, 8]]
arr3=np.array(list2, dtype='float')
print(arr3)
arr3_s = arr3.astype('int').astype('str')
print(arr3_s)
```

Out:
```
[[0. 1. 2.]
 [3. 4. 5.]
 [6. 7. 8.]]
[['0' '1' '2']
 ['3' '4' '5']
 ['6' '7' '8']]
```

- Remember that, unlike lists, all items in an array have to be of the same type.

dtype='object'

- However, if you are uncertain about what data type your array will hold, or if you want to hold characters and numbers in the same array, you can set the dtype as 'object'.

```
In: arr_obj = np.array([1, 'a'], dtype='object')
    print(arr_obj)
```

```
Out: ['1' 'a']
```

The tolist() function

- You can always convert an array into a list using the tolist() command.

```
In:  arr_list = arr_obj.tolist()
     print(arr_list)
```

```
Out: [1, 'a']
```

Inspecting a NumPy array

- There are a range of functions built into NumPy that allow you to inspect different aspects of an array:

In:
```
import numpy as np
list2 = [[0, 1, 2], [3, 4, 5], [6, 7, 8]]
arr3=np.array(list2, dtype='float')
print('Shape:', arr3.shape)
print('Data type:', arr3.dtype)
print('Size:', arr3.size)
print('Num dimensions:', arr3.ndim)
```

Out:
```
Shape: (3, 3)
Data type: float64
Size: 9
Num dimensions: 2
```

Extracting specific items from an array

- You can extract portions of the array using indices, much like when you're working with lists.
- Unlike lists, however, arrays can optionally accept as many parameters in the square brackets as there are number of dimensions

In:

```
import numpy as np
list2 = [[0, 1, 2], [3, 4, 5], [6, 7, 8]]
arr3=np.array(list2, dtype='float')
print("whole:", arr3)
print("Part:", arr3[:2, :2])
```

Out:

```
whole: [[0. 1. 2.]
 [3. 4. 5.]
 [6. 7. 8.]]
Part: [[0. 1.]
 [3. 4.]]
```

Boolean indexing

- A boolean index array is of the same shape as the array-to-be-filtered, but it only contains TRUE and FALSE values.

```
In: import numpy as np
    list2 = [[0, 1, 2], [3, 4, 5], [6, 7, 8]]
    arr3=np.array(list2, dtype='float')
    boo = arr3>2
    print(boo)
```

```
Out: [[False False False]
      [ True  True  True]
      [ True  True  True]]
```

Pandas

- Pandas, like NumPy, is one of the most popular Python libraries for data analysis.
- It is a high-level abstraction over low-level NumPy, which is written in pure C.
- Pandas provides high-performance, easy-to-use data structures and data analysis tools.
- There are two main structures used by pandas; *data frames* and *series*.

Indices in a pandas series

- A pandas series is similar to a list, but differs in the fact that a series associates a label with each element. This makes it look like a dictionary.
- If an index is not explicitly provided by the user, pandas creates a RangeIndex ranging from 0 to *N*-1.
- Each series object also has a data type.

In:
```
import pandas as pd
new_series = pd.Series([5, 6, 7, 8, 9, 10])
print(new_series)
```

Out:
```
0     5
1     6
2     7
3     8
4     9
5    10
dtype: int64
```

- As you may suspect by this point, a series has ways to extract all of the values in the series, as well as individual elements by index.

```
In:  import pandas as pd
     new_series = pd.Series([5, 6, 7, 8, 9, 10])
     print(new_series.values)
     print('_____________')
     print(new_series[4])
```

```
Out:
[ 5  6  7  8  9 10]
_____________
9
```

- You can also provide an index manually.

```
In:  import pandas as pd
     new_series = pd.Series([5, 6, 7, 8, 9, 10], index=['a', 'b', 'c', 'd', 'e', 'f'])
     print(new_series.values)
     print('_____________')
     print(new_series['f'])
```

```
Out:
[ 5  6  7  8  9 10]
_____________
10
```

- It is easy to retrieve several elements of a series by their indices or make group assignments.

In:

```
import pandas as pd
new_series = pd.Series([5, 6, 7, 8, 9, 10], index=['a', 'b', 'c', 'd', 'e', 'f'])
print(new_series)
print('_____________')
new_series[['a', 'b', 'f']] = 0
print(new_series)
```

Out:

```
a     5
b     6
c     7
d     8
e     9
f    10
dtype: int64
_____________
a    0
b    0
c    7
d    8
e    9
f    0
dtype: int64
```

Filtering and maths operations

- Filtering and maths operations are easy with Pandas as well.

In:
```
import pandas as pd
new_series = pd.Series([5, 6, 7, 8, 9, 10], index=['a', 'b', 'c', 'd', 'e', 'f'])
new_series2 = new_series[new_series>0]
print(new_series2)
print('_____________')
new_series2[new_series2>0]*2
print(new_series2)
```

Out:
```
a     5
b     6
c     7
d     8
e     9
f    10
dtype: int64
_____________
a     5
b     6
c     7
d     8
e     9
f    10
dtype: int64
```

Pandas data frame

- Simplistically, a data frame is a table, with rows and columns.
- Each column in a data frame is a series object.
- Rows consist of elements inside series.

Case ID	Variable one	Variable two	Variable 3
1	123	ABC	10
2	456	DEF	20
3	789	XYZ	30

Creating a Pandas data frame

- Pandas data frames can be constructed using Python dictionaries.

In:
```
import pandas as pd
df = pd.DataFrame({
    'country': ['Kazakhstan', 'Russia', 'Belarus', 'Ukraine'],
    'population': [17.04, 143.5, 9.5, 45.5],
    'square': [2724902, 17125191, 207600, 603628]})
print(df)
```

Out:

	country	population	square
0	Kazakhstan	17.04	2724902
1	Russia	143.50	17125191
2	Belarus	9.50	207600
3	Ukraine	45.50	603628

- You can also create a data frame from a list.

In:

```
import pandas as pd
list2 = [[0,1,2],[3,4,5],[6,7,8]]
df = pd.DataFrame(list2)
print(df)
df.columns = ['V1', 'V2', 'V3']
print(df)
```

Out:

```
In [12]: runfile('
   0  1  2
0  0  1  2
1  3  4  5
2  6  7  8
   V1  V2  V3
0   0   1   2
1   3   4   5
2   6   7   8
```

- You can ascertain the type of a column with the type() function.

```
In:  print(type(df['country']))

Out: <class 'pandas.core.series.Series'>
```

- A Pandas data frame object as two indices; a column index and row index.
- Again, if you do not provide one, Pandas will create a RangeIndex from 0 to *N*-1.

In:
```
import pandas as pd
df = pd.DataFrame({
    'country': ['Kazakhstan', 'Russia', 'Belarus', 'Ukraine'],
    'population': [17.04, 143.5, 9.5, 45.5],
    'square': [2724902, 17125191, 207600, 603628]})
print(df.columns)
print('__________')
print(df.index)
```

Out:
```
Index(['country', 'population', 'square'], dtype='object')

__________
RangeIndex(start=0, stop=4, step=1)
```

- There are numerous ways to provide row indices explicitly.
- For example, you could provide an index when creating a data frame:

In:
```
import pandas as pd
df = pd.DataFrame({
    'country': ['Kazakhstan', 'Russia', 'Belarus', 'Ukraine'],
    'population': [17.04, 143.5, 9.5, 45.5],
     'square': [2724902, 17125191, 207600, 603628]
}, index=['KZ', 'RU', 'BY', 'UA'])
print(df)
```

Out:

	country	population	square
KZ	Kazakhstan	17.04	2724902
RU	Russia	143.50	17125191
BY	Belarus	9.50	207600
UA	Ukraine	45.50	603628

- or do it during runtime.
- Here, I also named the index ‘country code’.

In:
```
import pandas as pd
df = pd.DataFrame({
    'country': ['Kazakhstan', 'Russia', 'Belarus', 'Ukraine'],
    'population': [17.04, 143.5, 9.5, 45.5],
     'square': [2724902, 17125191, 207600, 603628]
})
print(df)
print('_____________')
df.index = ['KZ', 'RU', 'BY', 'UA']
df.index.name = 'Country Code'
print(df)
```

Out:

	country	population	square
0	Kazakhstan	17.04	2724902
1	Russia	143.50	17125191
2	Belarus	9.50	207600
3	Ukraine	45.50	603628

____

Country Code	country	population	square
KZ	Kazakhstan	17.04	2724902
RU	Russia	143.50	17125191
BY	Belarus	9.50	207600
UA	Ukraine	45.50	603628

- Row access using index can be performed in several ways.
- First, you could use .loc() and provide an index label.

```
In:  print(df.loc['KZ'])
```

```
Out: country       Kazakhstan
     population         17.04
     square           2724902
     Name: KZ, dtype: object
```

- Second, you could use .iloc() and provide an index number

```
In:  print(df.iloc[0])
```

```
Out: country       Kazakhstan
     population         17.04
     square           2724902
     Name: KZ, dtype: object
```

- A selection of particular rows and columns can be selected this way.

```
In: print(df.loc[['KZ', 'RU'], 'population'])
```

```
Out: Country Code
KZ     17.04
RU    143.50
Name: population, dtype: float64
```

- You can feed .loc() two arguments, index list and column list, slicing operation is supported as well:

```
In: print(df.loc['KZ':'BY', :])
```

```
Out:
              country  population    square
Country Code
KZ         Kazakhstan       17.04   2724902
RU             Russia      143.50  17125191
BY            Belarus        9.50    207600
```

Filtering

- Filtering is performed using so-called Boolean arrays.

```
print(df[df.population > 10][['country', 'square']])
```

Country Code	country	square
KZ	Kazakhstan	2724902
RU	Russia	17125191
UA	Ukraine	603628

Deleting columns

- You can delete a column using the drop() function.

```
In:  print(df)
```

```
Out:
                country  population    square
Country Code
KZ           Kazakhstan       17.04   2724902
RU               Russia      143.50  17125191
BY              Belarus        9.50    207600
UA              Ukraine       45.50    603628
```

```
In:  df = df.drop(['population'], axis='columns')
     print(df)
```

```
Out:
                country    square
Country Code
KZ           Kazakhstan   2724902
RU               Russia  17125191
BY              Belarus    207600
UA              Ukraine    603628
```

Reading from and writing to a file

- Pandas supports many popular file formats including CSV, XML, HTML, Excel, SQL, JSON, etc.
- Out of all of these, CSV is the file format that you will work with the most.
- You can read in the data from a CSV file using the read_csv() function.

```
df = pd.read_csv('filename.csv', sep=',')
```

- Similarly, you can write a data frame to a csv file with the to_csv() function.

```
df.to_csv('filename.csv')
```

- Pandas has the capacity to do much more than what we have covered here, such as grouping data and even data visualisation.
- However, as with NumPy, we don’t have enough time to cover every aspect of pandas here.

Exploratory data analysis (EDA)

Exploring your data is a crucial step in data analysis. It involves:

- Organising the data set
- Plotting aspects of the data set
- Maybe producing some numerical summaries; central tendency and spread, etc.

"Exploratory data analysis can never be the whole story, but nothing else can serve as the foundation stone."
- John Tukey.

Download the data

- Download the Pokemon dataset from:

https://github.com/LewBrace/da_and_vis_python

- Unzip the folder, and save the data file in a location you'll remember.

Reading in the data

- First we import the Python packages we are going to use.
- Then we use Pandas to load in the dataset as a data frame.

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
df1 = pd.read_csv('C:/Users/lb690/Google Drive/Teaching/Q-Step_workshops_2019_2020/pokemon_dataset.csv', index_col=0, encoding = "ISO-8859-1")
```

NOTE: The argument `index_col` argument states that we'll treat the first column of the dataset as the ID column.

NOTE: The encoding argument allows us to by pass an input error created by special characters in the data set.

Examine the data set

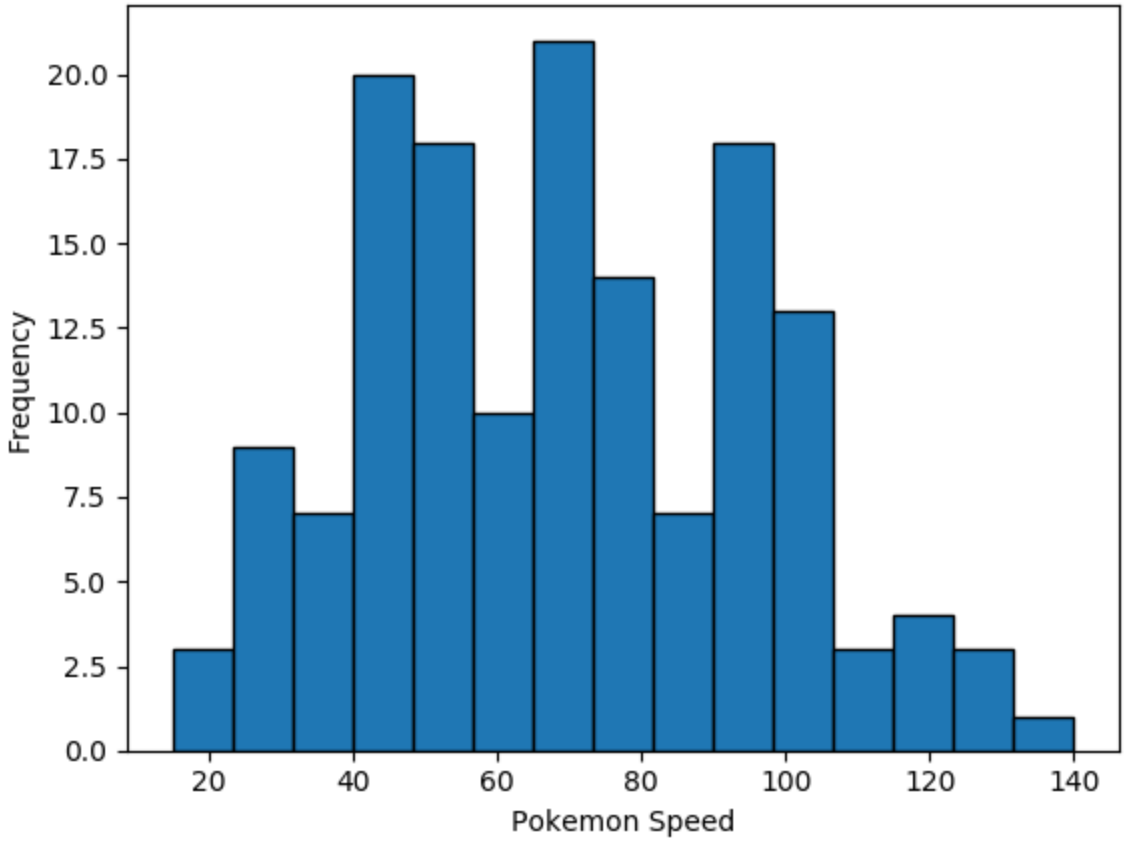
```
print(df1.head())
```

```
          Name Type 1  Type 2  Total  ...  Sp. Def  Speed  Stage  Legendary
#                                      ...
1    Bulbasaur  Grass  Poison    318  ...       65     45      1      False
2      Ivysaur  Grass  Poison    405  ...       80     60      2      False
3     Venusaur  Grass  Poison    525  ...      100     80      3      False
4   Charmander   Fire     NaN    309  ...       50     65      1      False
5   Charmeleon   Fire     NaN    405  ...       65     80      2      False
```

```
print(df1.describe())
```

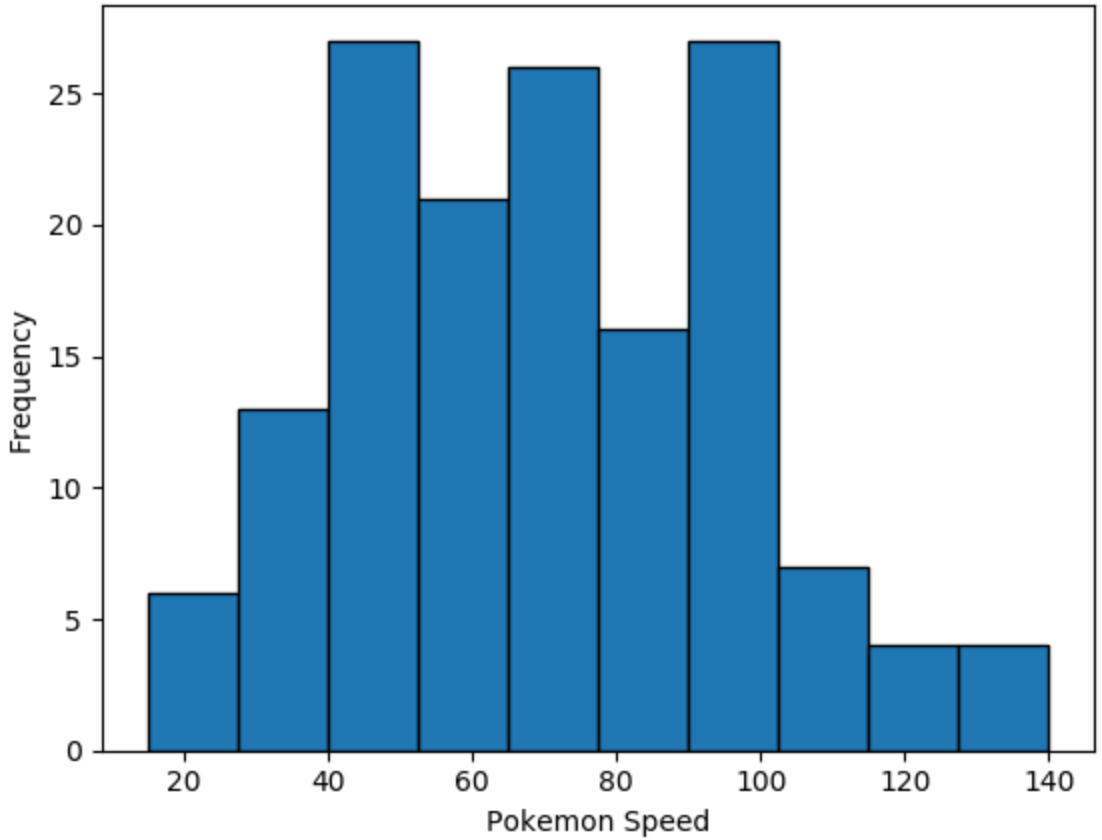
```
            Total          HP      Attack  ...     Sp. Def       Speed       Stage
count  151.00000  151.000000  151.000000  ...  151.000000  151.000000  151.000000
mean   407.07947   64.211921   72.549669  ...   66.019868   68.933775    1.582781
std     99.74384   28.590117   26.596162  ...   24.197926   26.746880    0.676832
min    195.00000   10.000000    5.000000  ...   20.000000   15.000000    1.000000
25%    320.00000   45.000000   51.000000  ...   49.000000   46.500000    1.000000
50%    405.00000   60.000000   70.000000  ...   65.000000   70.000000    1.000000
75%    490.00000   80.000000   90.000000  ...   80.000000   90.000000    2.000000
max    680.00000  250.000000  134.000000  ...  125.000000  140.000000    3.000000
```

- We could spend time staring at these numbers, but that is unlikely to offer us any form of insight.
- We could begin by conducting all of our statistical tests.
- However, a good field commander never goes into battle without first doing a recognisance of the terrain…
- This is exactly what EDA is for…



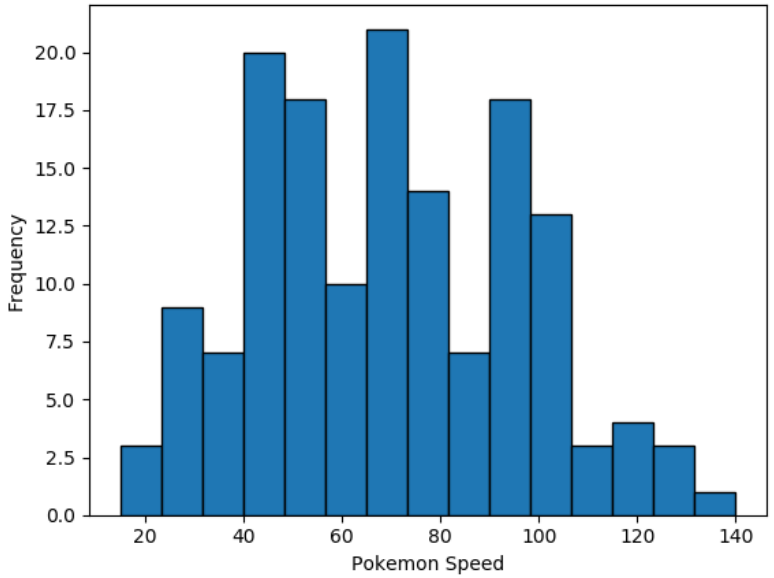
Plotting a histogram in Python

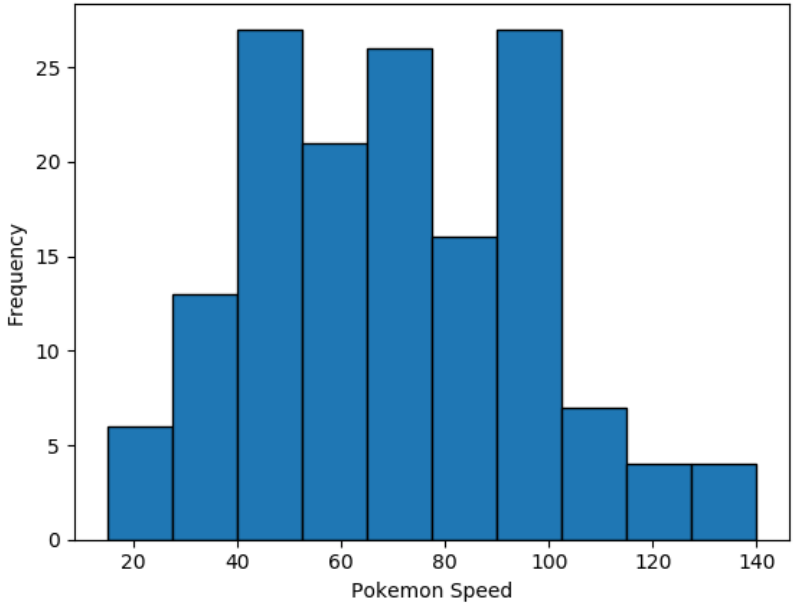
```
g = plt.hist(df1['Speed'], histtype='bar', ec='black',)
g = plt.xlabel('Pokemon Speed')
g = plt.ylabel('Frequency')
plt.show()
```



Bins

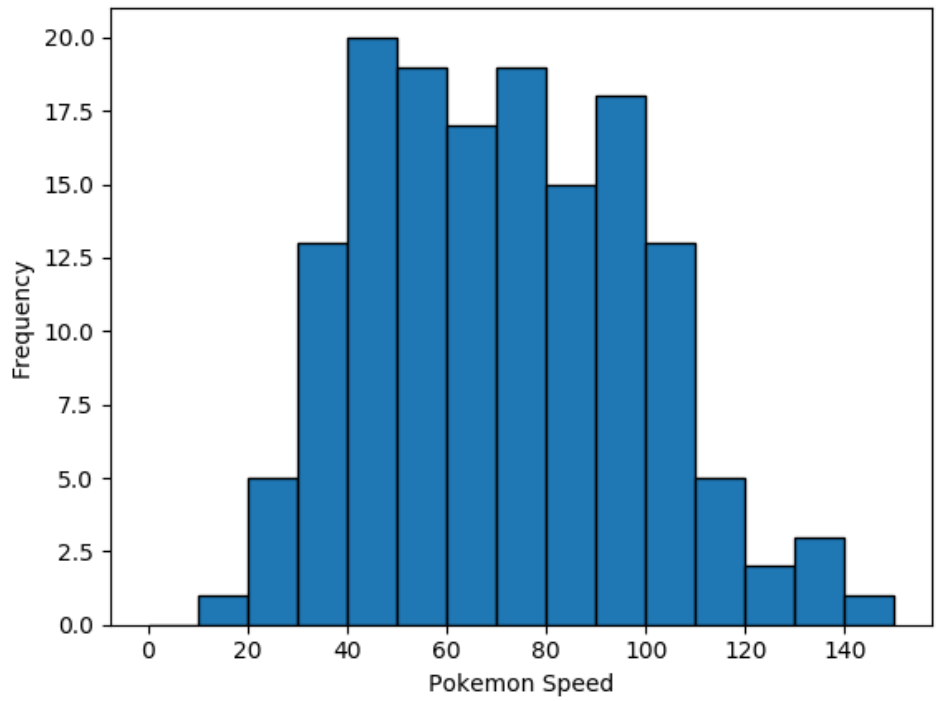
- You may have noticed the two histograms we've seen so far look different, despite using the **exact** same data.
- This is because they have different bin values.
- The left graph used the default bins generated by `plt.hist()`, while the one on the right used bins that I specified.





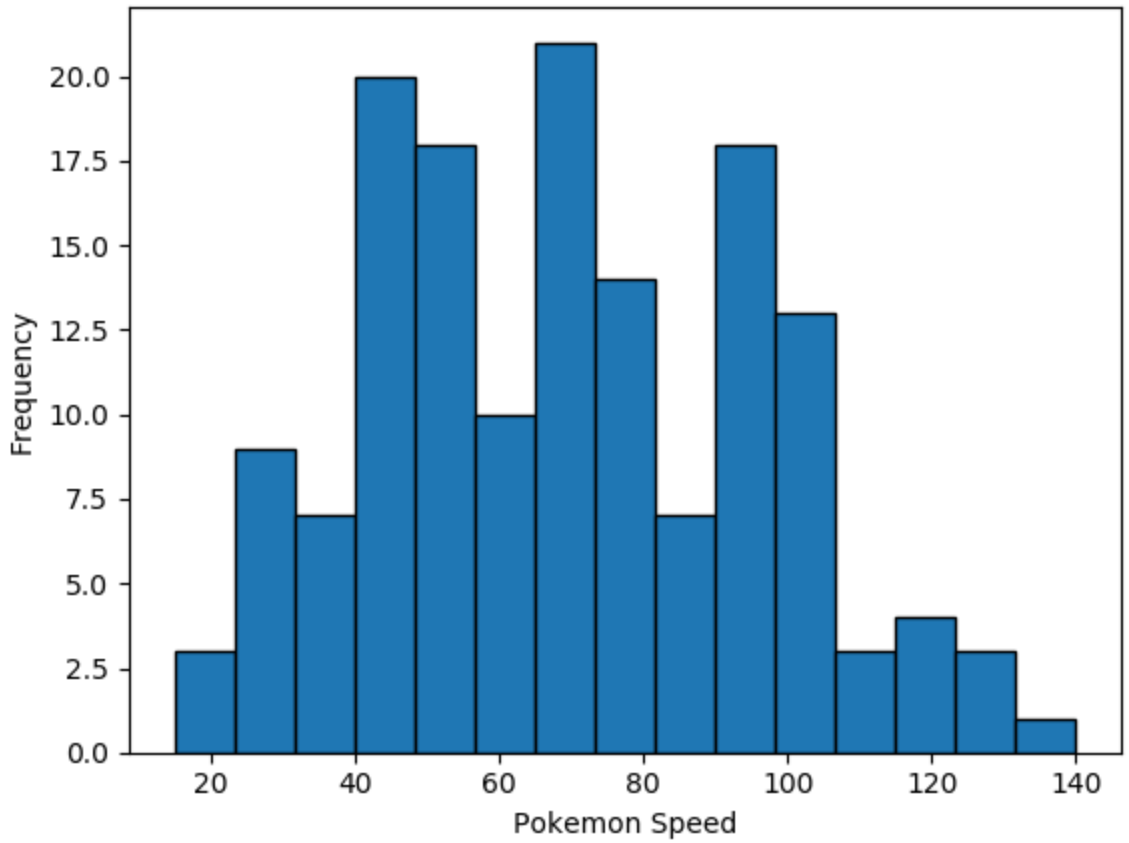
- There are a couple of ways to manipulate bins in matplotlib.
- Here, I specified where the edges of the bars of the histogram are; the bin edges.

```
bin_edges = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150]
g = plt.hist(df1['Speed'], histtype='bar', ec='black', bins=bin_edges)
g = plt.xlabel('Pokemon Speed')
g = plt.ylabel('Frequency')
plt.show()
```



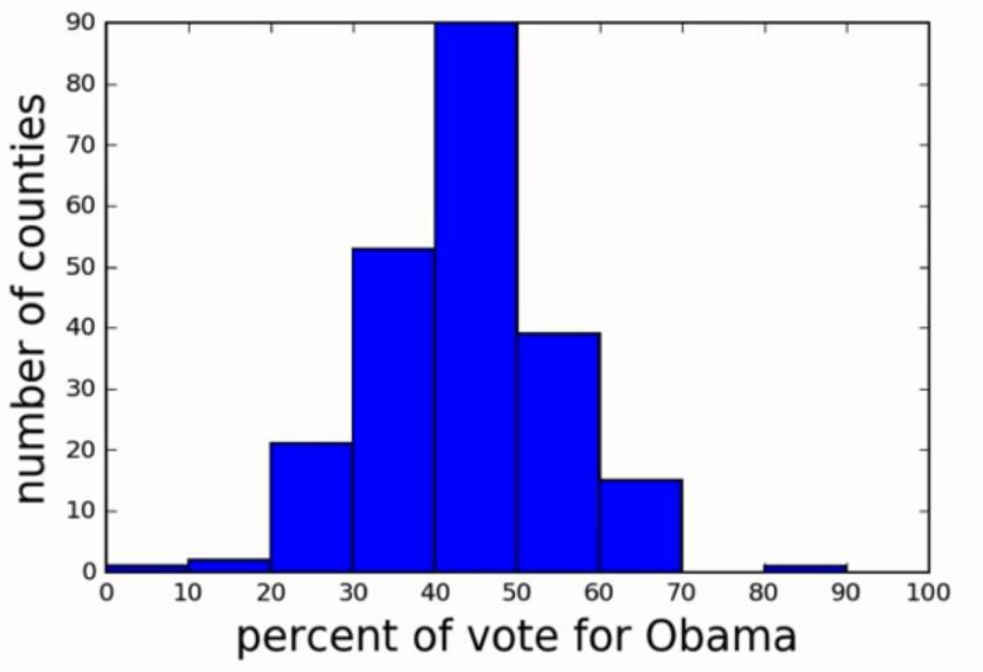
- You could also specify the number of bins, and Matplotlib will automatically generate a number of evenly spaced bins.

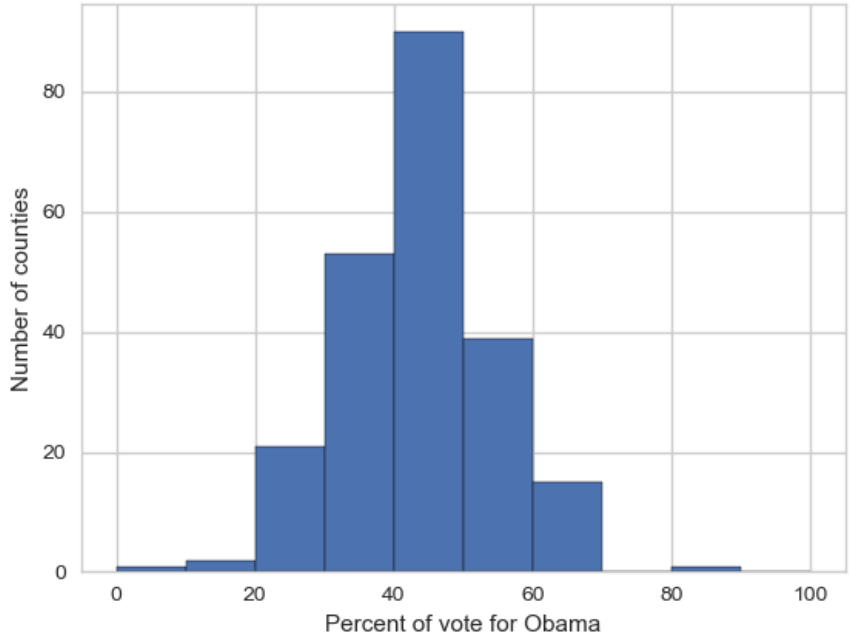
```
g = plt.hist(df1['Speed'], histtype='bar', ec='black', bins=15)
g = plt.xlabel('Pokemon Speed')
g = plt.ylabel('Frequency')
plt.show()
```



Seaborn

- Matplotlib is a powerful, but sometimes unwieldy, Python library.
- Seaborn provides a high-level interface to Matplotlib and makes it easier to produce graphs like the one on the right.
- Some IDEs incorporate elements of this “under the hood” nowadays.





Benefits of Seaborn

- Seaborn offers:
    - Using default themes that are aesthetically pleasing.
    - Setting custom colour palettes.
    - Making attractive statistical plots.
    - Easily and flexibly displaying distributions.
    - Visualising information from matrices and DataFrames.
- The last three points have led to Seaborn becoming the exploratory data analysis tool of choice for many Python users.

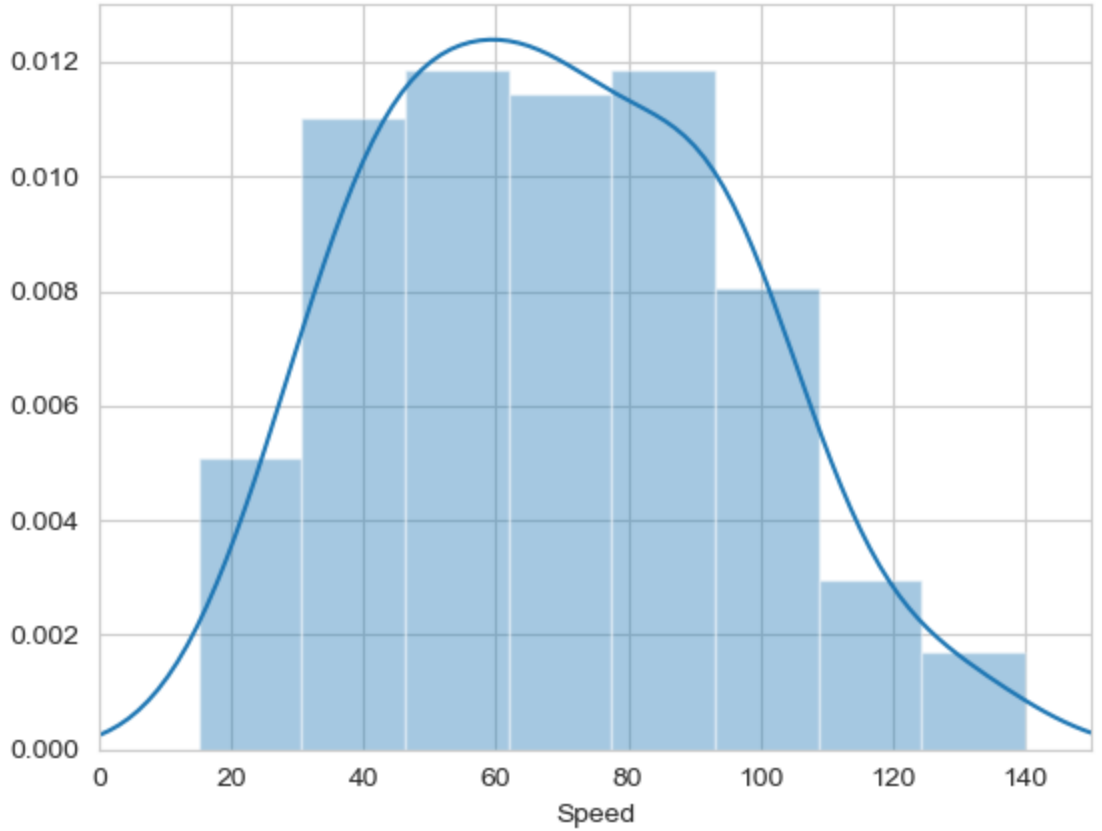
Plotting with Seaborn

- One of Seaborn's greatest strengths is its diversity of plotting functions.
- Most plots can be created with one line of code.
- For example….

Histograms

- Allow you to plot the distributions of numeric variables.

```
sns.set_style()
sns.distplot(df1.Speed)
```



Other types of graphs: Creating a scatter plot

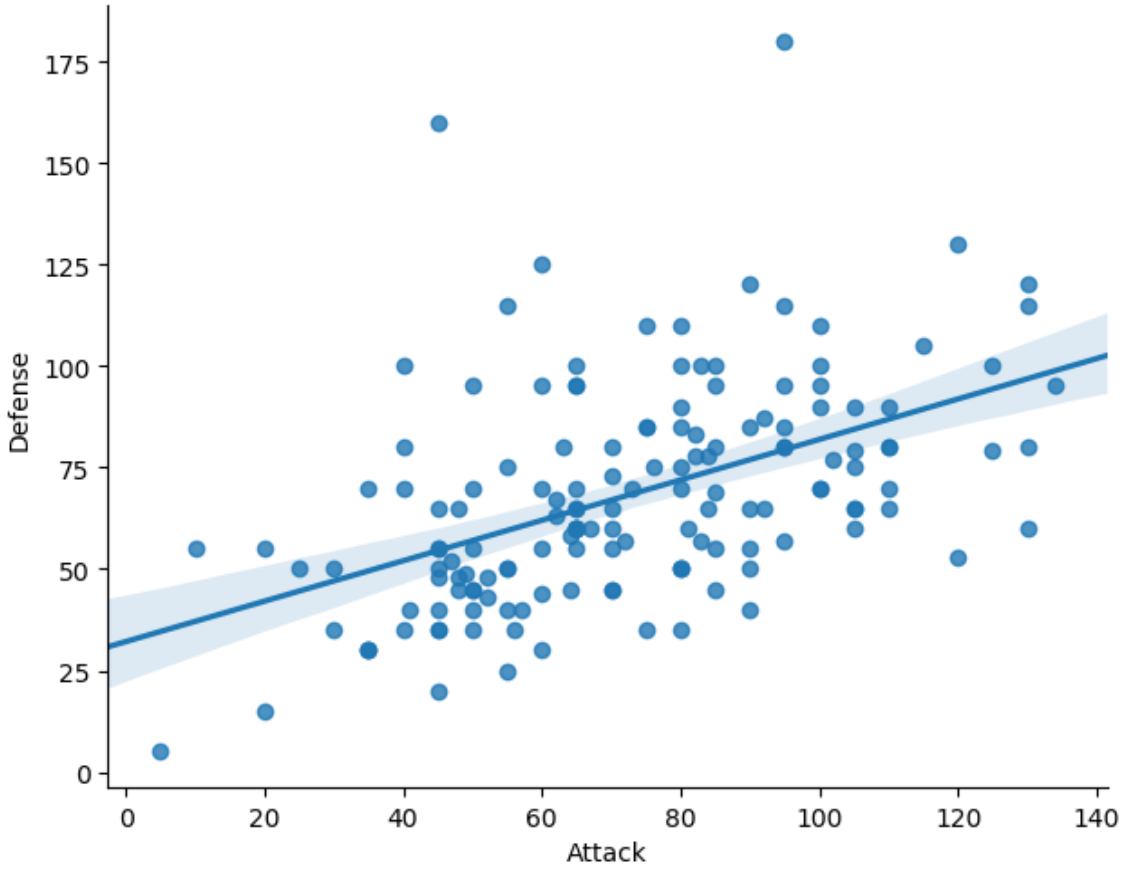
Name of variable we want on the x-axis

Name of our dataframe fed to the "data=" command

```
sns.lmplot(x='Attack', y='Defense', data=df1)
```

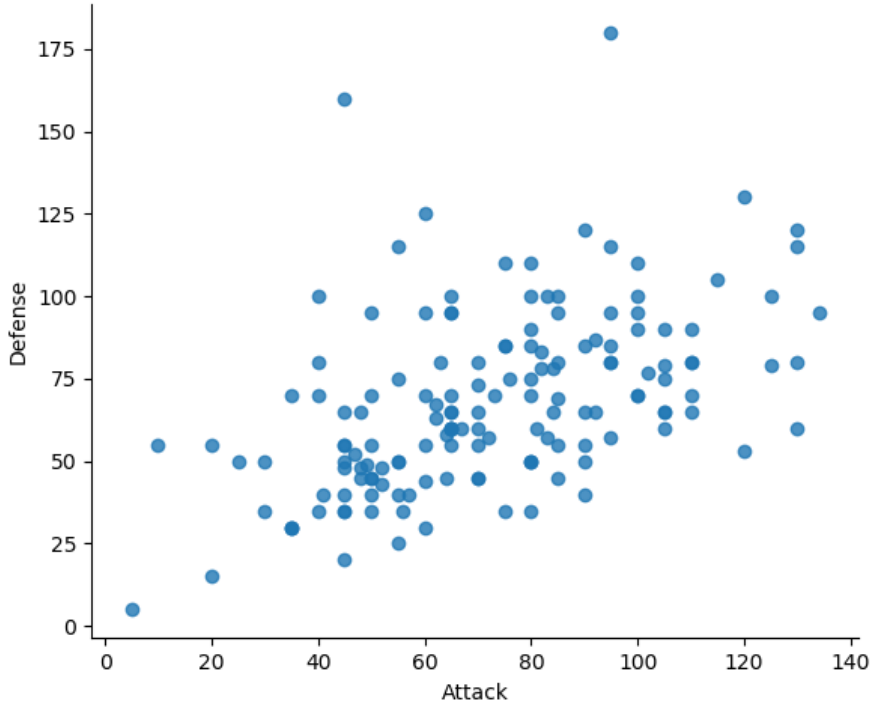
Seaborn "linear model plot" function for creating a scatter graph

Name of variable we want on the y-axis



- Seaborn doesn't have a dedicated scatter plot function.
- We used Seaborn's function for fitting and plotting a regression line; hence lmplot()
- However, Seaborn makes it easy to alter plots.
- To remove the regression line, we use the fit_reg=False command

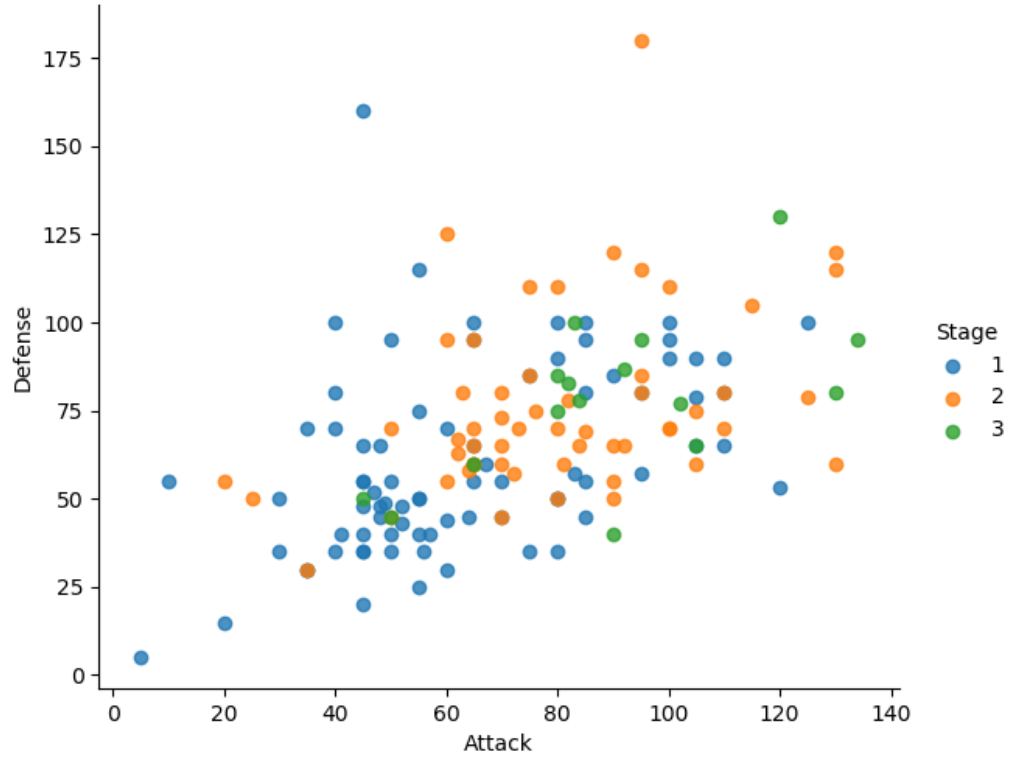
```
sns.lmplot(x='Attack', y='Defense', data=df1, fit_reg=False)
```



The hue function

- Another useful function in Seaborn is the hue function, which enables us to use a variable to colour code our data points.

```
sns.lmplot(x='Attack', y='Defense', data=df1,
           fit_reg=False,
           hue='Stage')
```



Factor plots

- Make it easy to separate plots by categorical classes.

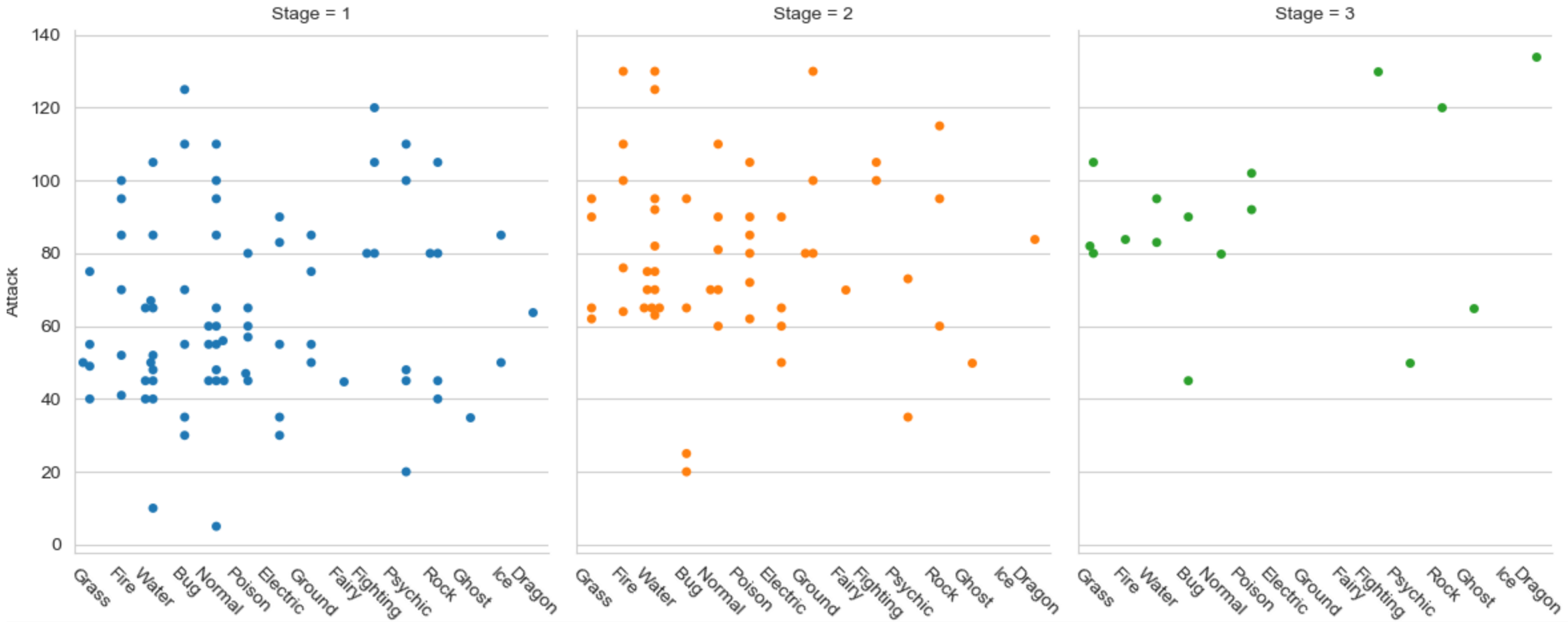
```
g = sns.factorplot(x='Type 1',
                   y='Attack',
                   data=df1,
                   hue='Stage',
                   col='Stage',
                   kind='swarm')
g.set_xticklabels(rotation=-45)
```

Colour by stage.

Separate by stage.

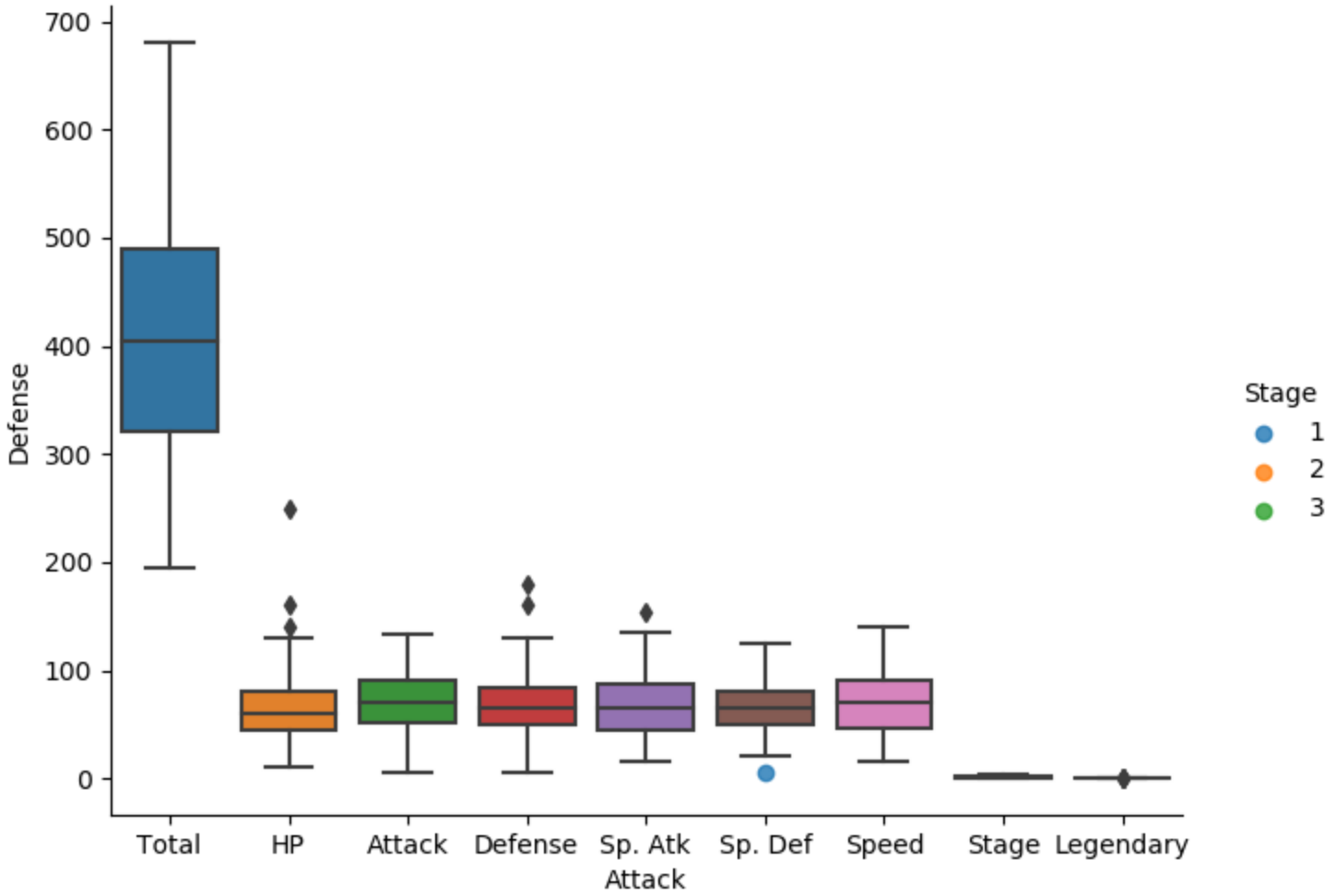
Generate using a swarmplot.

Rotate axis on x-ticks by 45 degrees.


Stage = 1
Stage = 2
Stage = 3
Attack
140
120
100
80
60
40
20
0
Grass
Fire
Water
Bug
Normal
Poison
Electric
Ground
Fairy
Fighting
Psychic
Rock
Ghost
Ice
Dragon

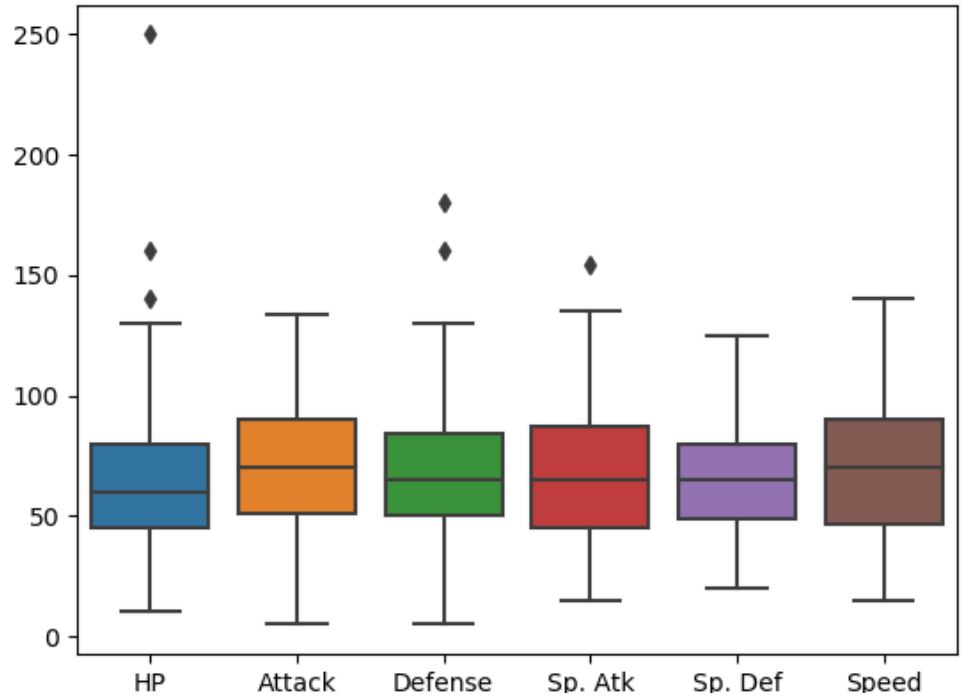
A box plot

```
sns.boxplot(data=df1)
```



- The total, stage, and legendary entries are not combat stats so we should remove them.
- Pandas makes this easy to do, we just create a new dataframe
- We just use Pandas' .drop() function to create a dataframe that doesn't include the variables we don't want.

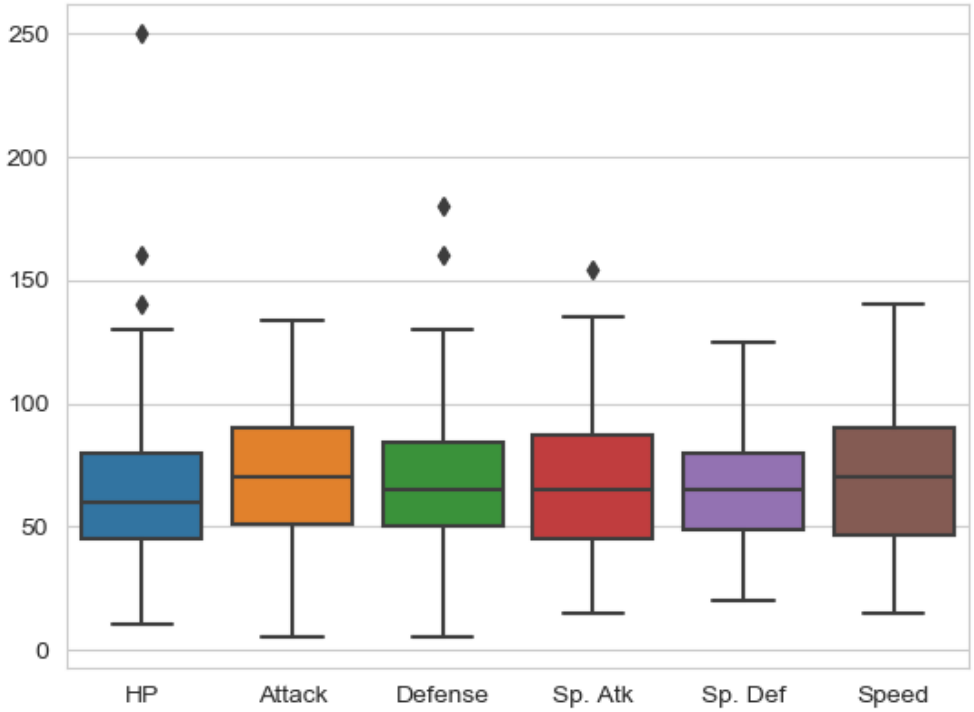
```
stats_df = df1.drop(['Total', 'Stage', 'Legendary'], axis=1)
sns.boxplot(data=stats_df)
```



Seaborn's theme

- Seaborn has a number of themes you can use to alter the appearance of plots.
- For example, we can use "whitegrid" to add grid lines to our boxplot.

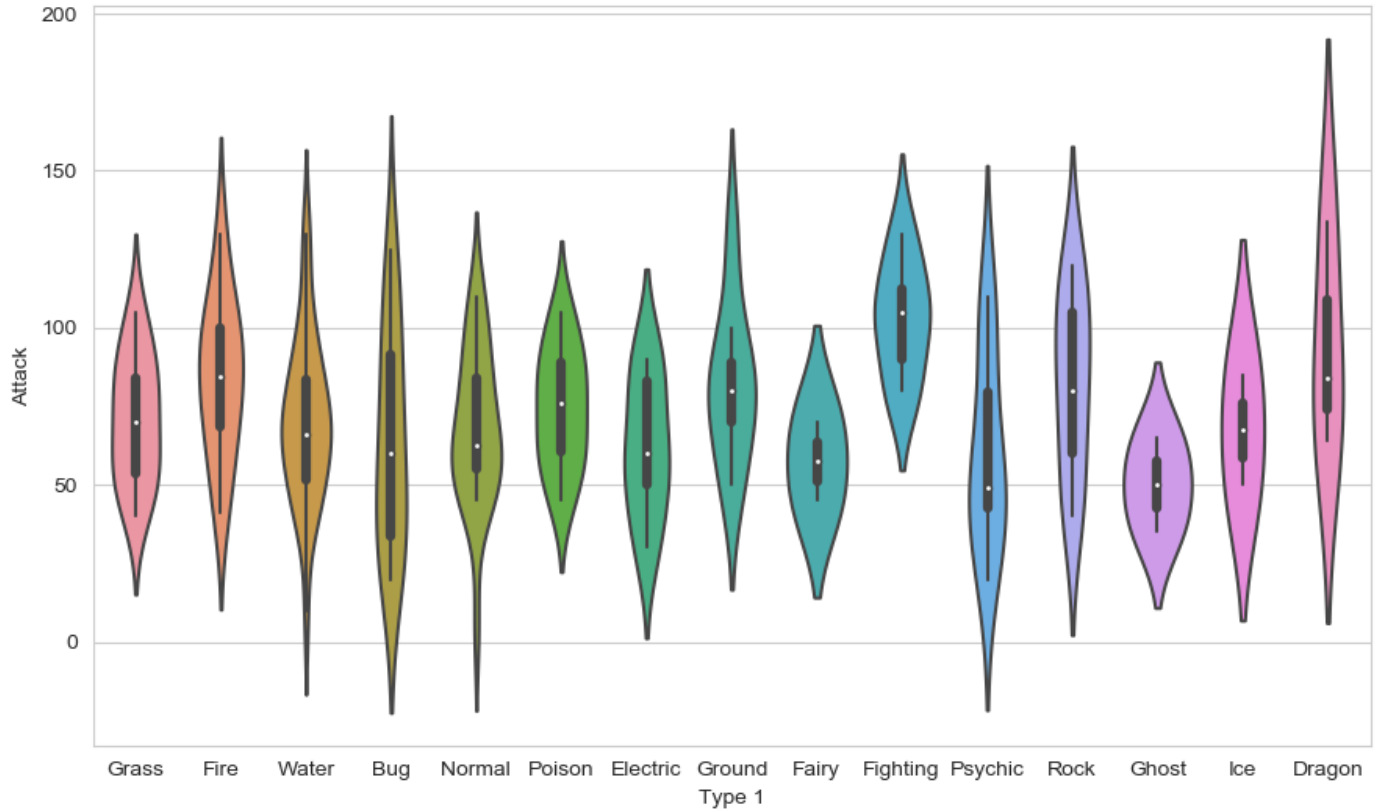
```
stats_df = df1.drop(['Total', 'Stage', 'Legendary'], axis=1)
sns.set_style('whitegrid')
sns.boxplot(data=stats_df)
```



Violin plots

- Violin plots are useful alternatives to box plots.
- They show the distribution of a variable through the thickness of the violin.
- Here, we visualise the distribution of attack by Pokémon's primary type:

```
sns.violinplot(x='Type 1', y='Attack', data=df1)
```



- Dragon types tend to have higher Attack stats than Ghost types, but they also have greater variance. But there is something not right here….
- The colours!

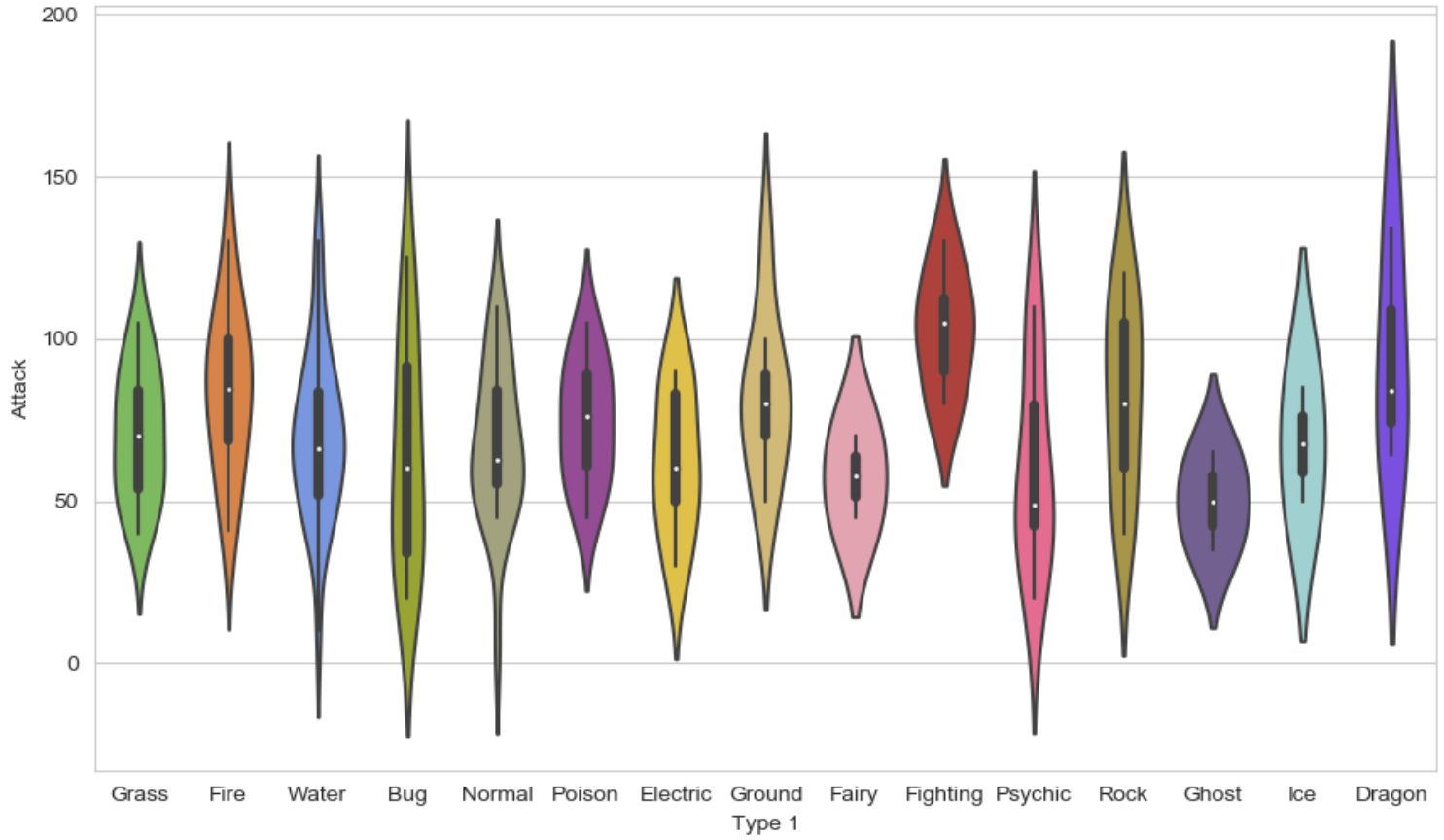
Seaborn’s colour palettes

- Seaborn allows us to easily set custom colour palettes by providing it with an ordered list of colour hex values.
- We first create our colours list.

```
type_colors = ['#78C850',  # Grass
               '#F08030',  # Fire
               '#6890F0',  # Water
               '#A8B820',  # Bug
               '#A8A878',  # Normal
               '#A040A0',  # Poison
               '#F8D030',  # Electric
               '#E0C068',  # Ground
               '#EE99AC',  # Fairy
               '#C03028',  # Fighting
               '#F85888',  # Psychic
               '#B8A038',  # Rock
               '#705898',  # Ghost
               '#98D8D8',  # Ice
               '#7038F8',  # Dragon
              ]
```

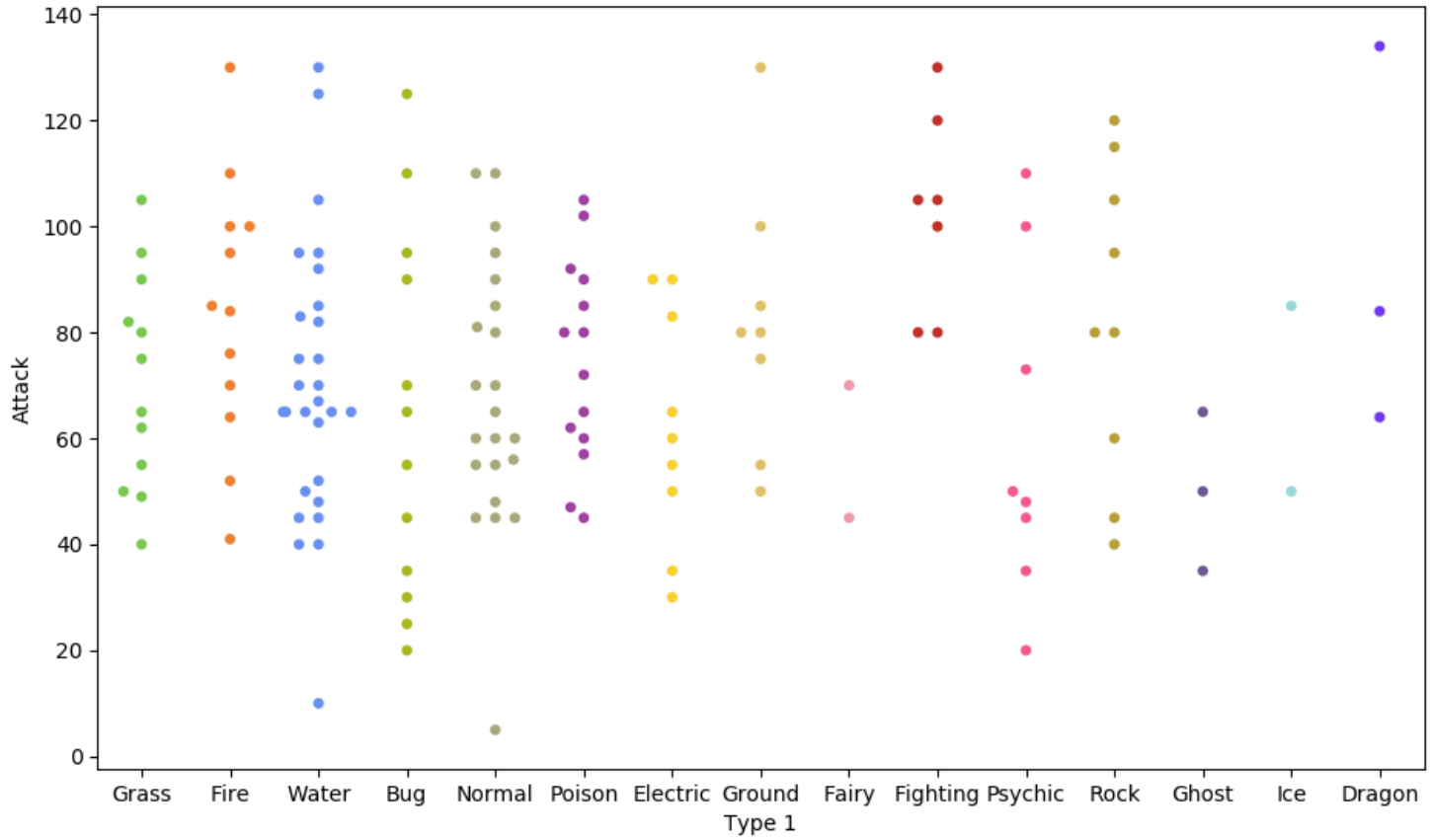
- Then we just use the palette= function and feed in our colours list.

```
sns.violinplot(x='Type 1', y='Attack', data=df1,
               palette=type_colors)
```



- Because of the limited number of observations, we could also use a swarm plot.
- Here, each data point is an observation, but data points are grouped together by the variable listed on the x-axis.

```
sns.swarmplot(x='Type 1', y='Attack',
              data=df1,
              palette=type_colors)
```



Overlapping plots

- Both of these show similar information, so it might be useful to overlap them.

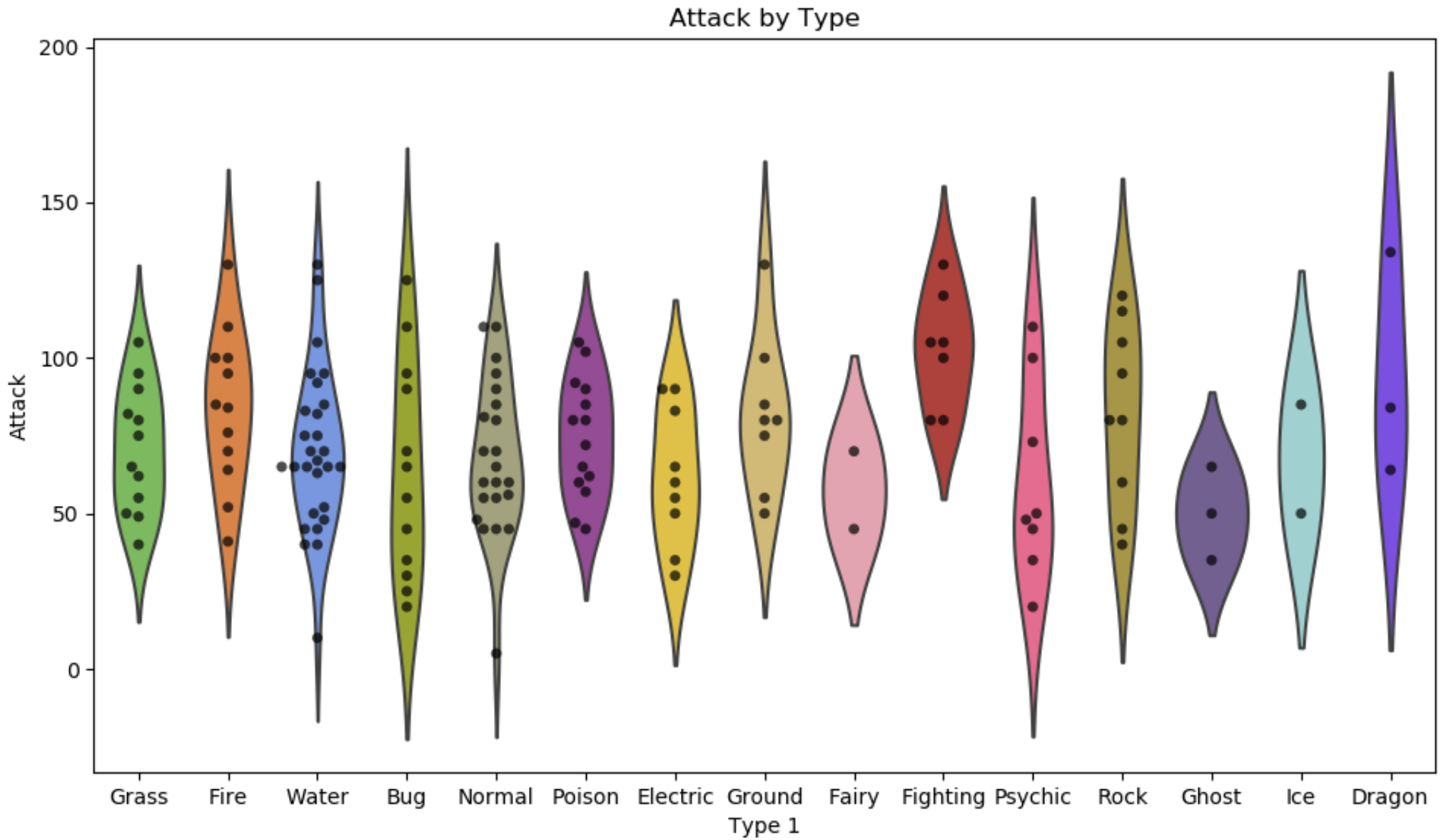
```
plt.figure(figsize=(10,6))
sns.violinplot(x='Type 1',
               y='Attack',
               data=df1,
               inner=None,
               palette=type_colors)
sns.swarmplot(x='Type 1',
              y='Attack',
              data=df1,
              color='k',
              alpha=0.7)
plt.title('Attack by Type')
```

Set size of print canvas.

Remove bars from inside the violins

Make bars black and slightly transparent

Give the graph a title


Attack by Type
Attack
200
150
100
50
0
Grass
Fire
Water
Bug
Normal
Poison
Electric
Ground
Fairy
Fighting
Psychic
Rock
Ghost
Ice
Dragon
Type 1

Data wrangling with Pandas

- What if we wanted to create such a plot that included all of the other stats as well?
- In our current dataframe, all of the variables are in different columns:

```
print(df1.head())
```

```
          Name Type 1  Type 2  Total  ...  Sp. Def  Speed  Stage  Legendary
#                                      ...
1    Bulbasaur  Grass  Poison    318  ...       65     45      1      False
2      Ivysaur  Grass  Poison    405  ...       80     60      2      False
3     Venusaur  Grass  Poison    525  ...      100     80      3      False
4   Charmander   Fire     NaN    309  ...       50     65      1      False
5   Charmeleon   Fire     NaN    405  ...       65     80      2      False
```

- If we want to visualise all stats, then we'll have to "melt" the dataframe.

```
stats_df = df1.drop(['Total', 'Stage', 'Legendary'], axis=1)
melted_df = pd.melt(stats_df,
                    id_vars=["Name", "Type 1", "Type 2"],
                    var_name="Stat")
print(melted_df.head())
```

We use the .drop() function again to re-create the dataframe without these three variables.

The dataframe we want to melt.

The variables to keep, all others will be melted.

A name for the new, melted, variable.

```
In [6]: runfile('C:/Users/lb690/Google Dri
pokemon_tutorial.py', wdir='C:/Users/lb690
          Name Type 1  Type 2 Stat  value
0    Bulbasaur  Grass  Poison   HP     45
1      Ivysaur  Grass  Poison   HP     60
2     Venusaur  Grass  Poison   HP     80
3   Charmander   Fire     NaN   HP     39
4   Charmeleon   Fire     NaN   HP     58
```

- All 6 of the stat columns have been "melted" into one, and the new Stat column indicates the original stat (HP, Attack, Defense, Sp. Attack, Sp. Defense, or Speed).
- It's hard to see here, but each pokemon now has 6 rows of data; hende the melted_df has 6 times more rows of data.

```
print( stats_df.shape )
print( melted_df.shape )
```

```
(151, 9)
(906, 5)
```

```
sns.swarmplot(x='Stat', y='value', data=melted_df,
hue='Type 1')
```

- This graph could be made to look nicer with a few tweaks.

```
plt.figure(figsize=(10,6))
sns.swarmplot(x='Stat',
              y='value',
              data=melted_df,
              hue='Type 1',
              split=True,
              palette=type_colors)
plt.ylim(0, 260)
plt.legend(bbox_to_anchor=(1, 1), loc=2)
```

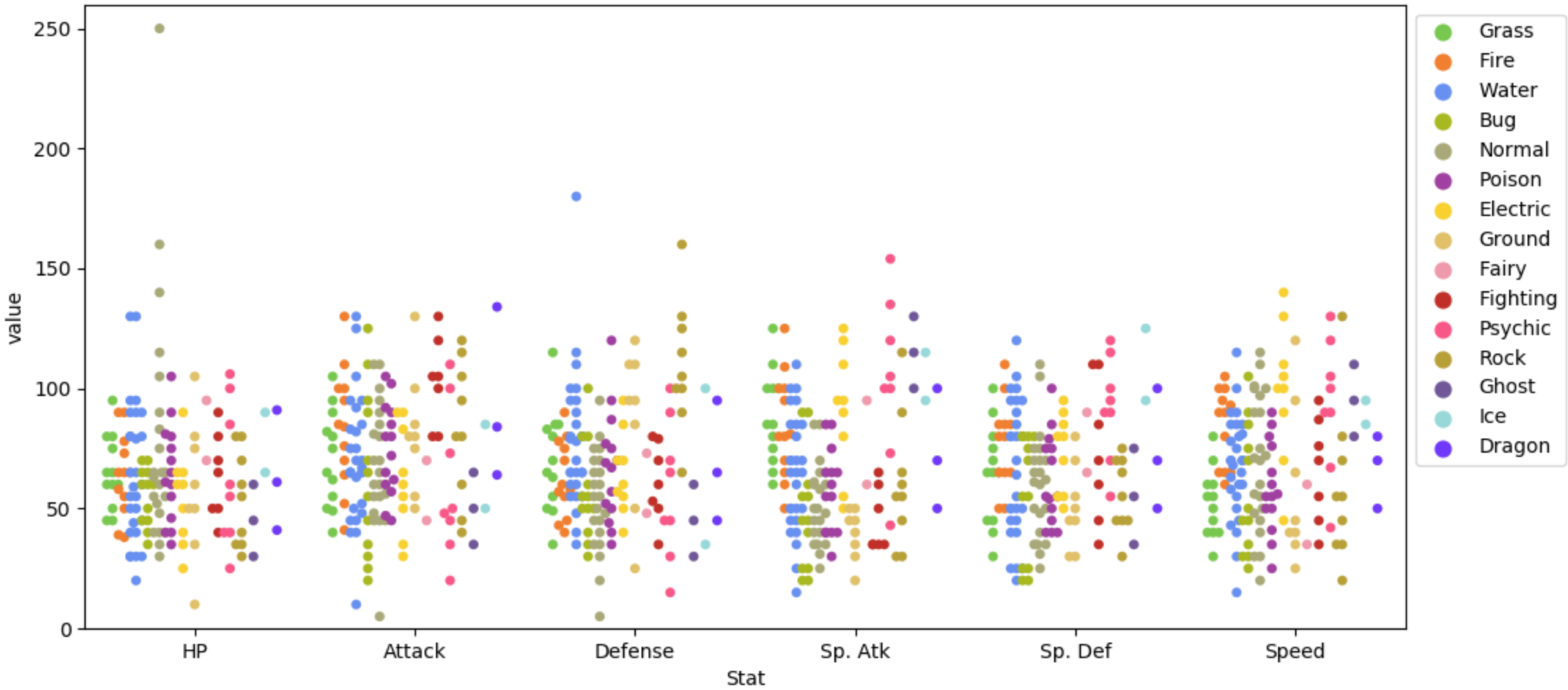
Enlarge the plot.

Separate points by hue.

Use our special Pokemon colour palette.

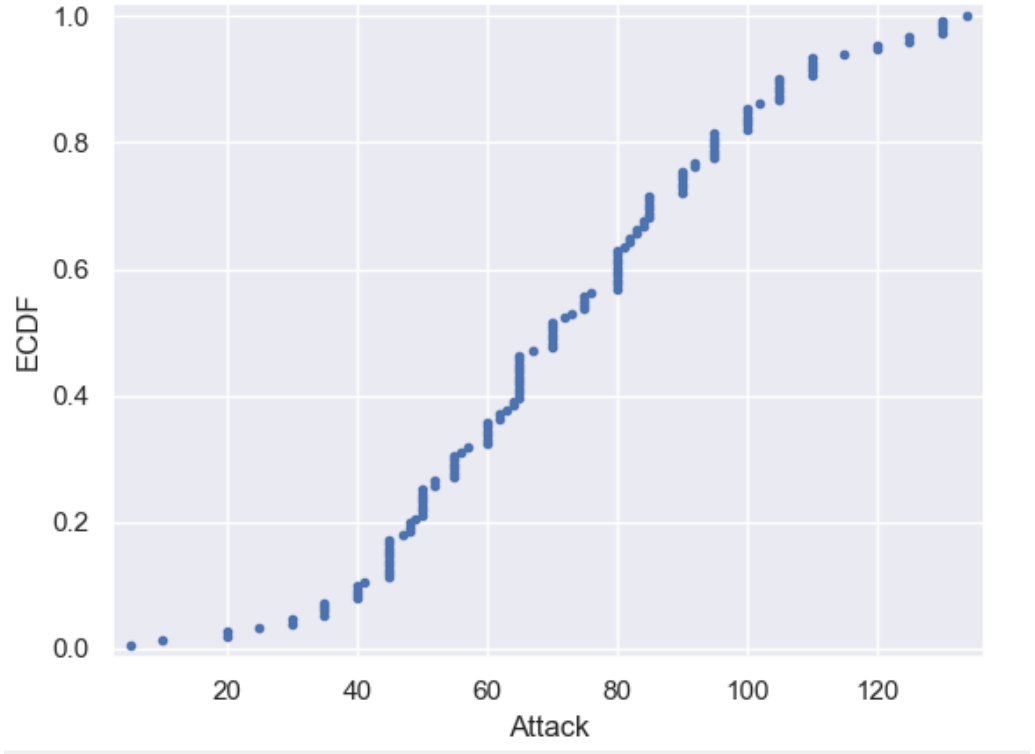
Adjust the y-axis.

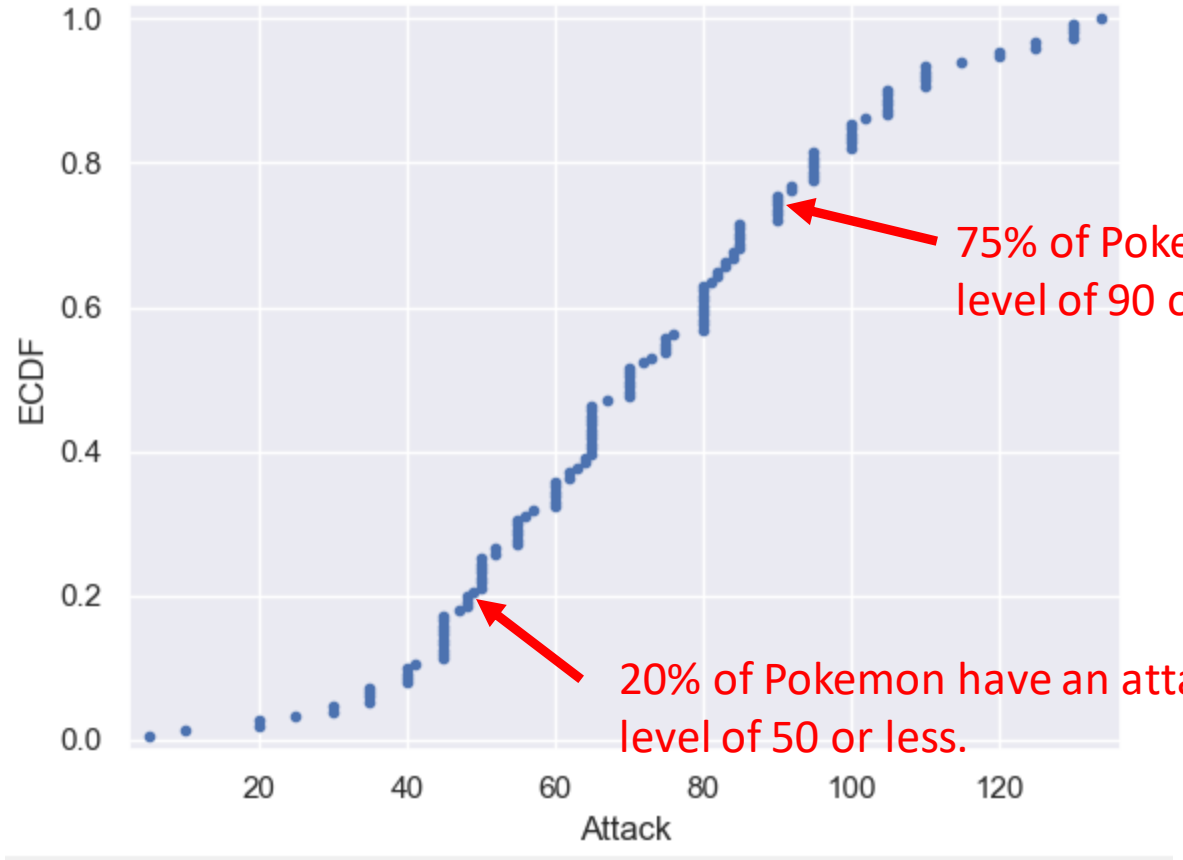
Move the legend box outside of the graph and place to the right of it..


250
200
150
100
50
0
value
HP
Attack
Defense
Sp. Atk
Sp. Def
Speed
Stat
Grass
Fire
Water
Bug
Normal
Poison
Electric
Ground
Fairy
Fighting
Psychic
Rock
Ghost
Ice
Dragon

Plotting all data: Empirical cumulative distribution functions (ECDFs)

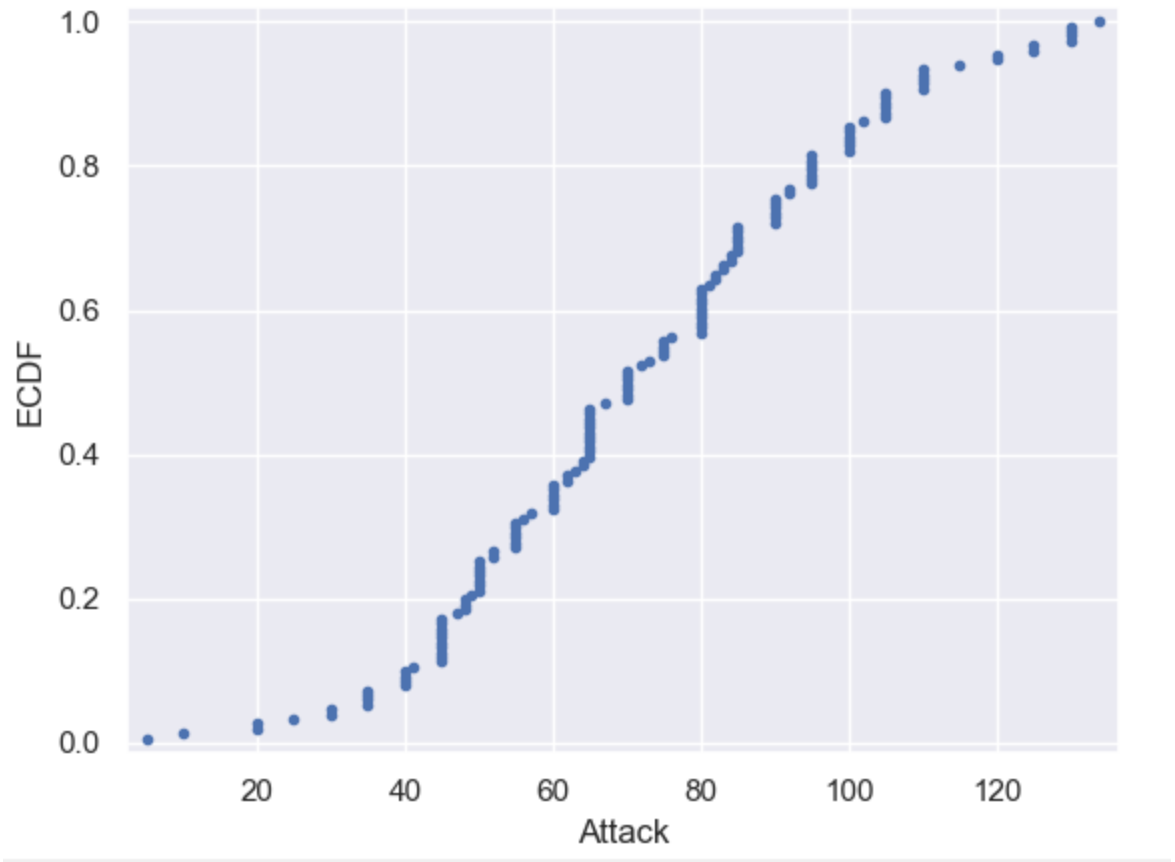
- An alternative way of visualising a distribution of a variable in a large dataset is to use an ECDF.
- Here we have an ECDF that shows the percentages of different attack strengths of pokemon.
- An *x-value* of an ECDF is the quantity you are measuring; i.e. attacks strength.
- The *y-value* is the fraction of data points that have a value smaller than the corresponding x-value. For example…



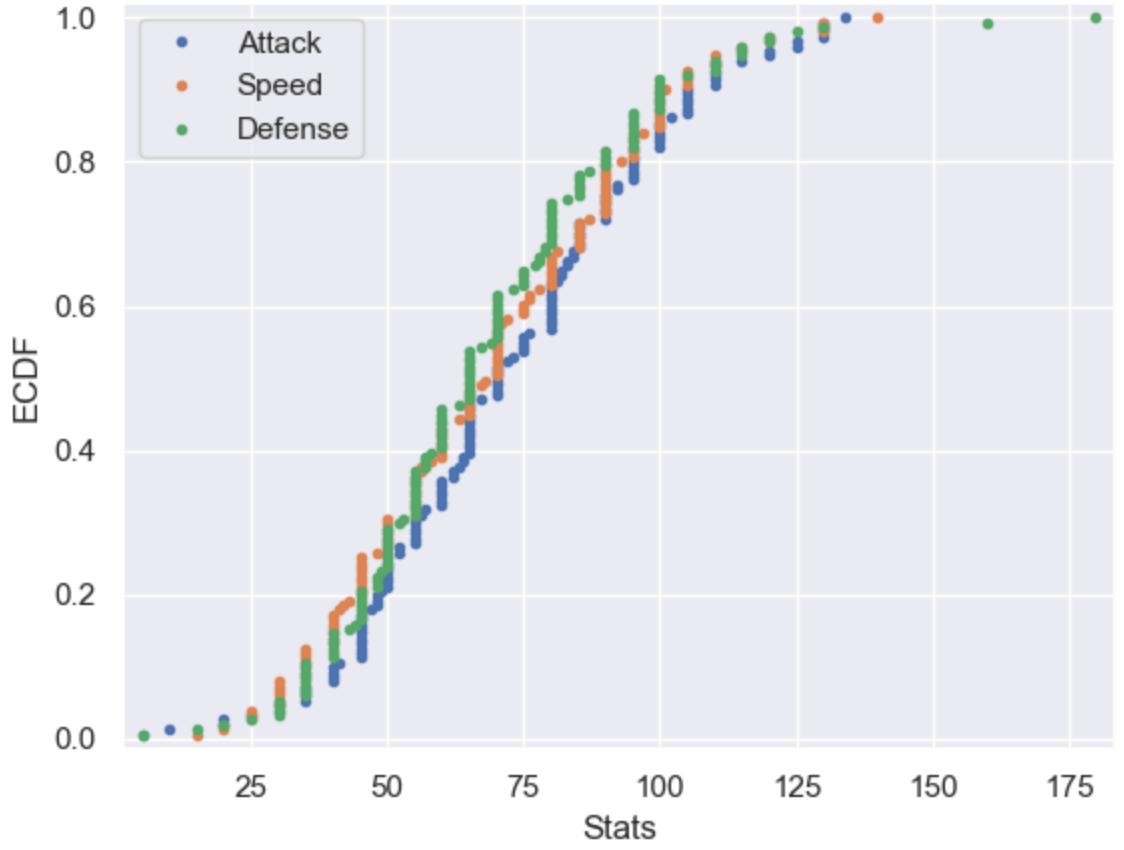

1.0
0.8
0.6
0.4
0.2
0.0
ECDF
20
40
60
80
100
120
Attack
75% of Pokemon have an attack level of 90 or less
20% of Pokemon have an attack level of 50 or less.

Plotting an ECDF

```
x = np.sort(df1['Attack'])
y=np.arange(1, len(x)+1)/len(x)
g = plt.plot(x, y, marker='.', linestyle='none')
g = plt.xlabel('Attack')
g = plt.ylabel('ECDF')
plt.margins(0.02)
plt.show()
```



- You can also plot multiple ECDFs on the same plot.
- As an example, here with have an ECDF for Pokemon attack, speed, and defence levels.
- We can see here that defence levels tend to be a little less than the other two.



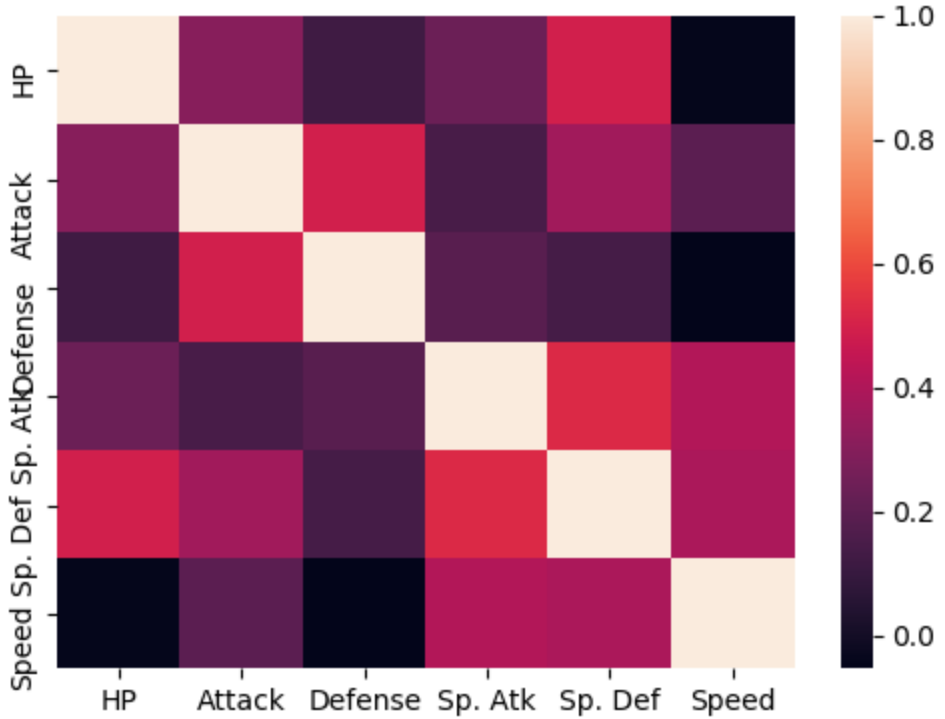
The usefulness of ECDFs

- It is often quite useful to plot the ECDF first as part of your workflow.
- It shows all the data and gives a complete picture as to how the data are distributed.

Heatmaps

- Useful for visualising matrix-like data.
- Here, we'll plot the correlation of the stats_df variables

```
corr = stats_df.corr()
sns.heatmap(corr)
```

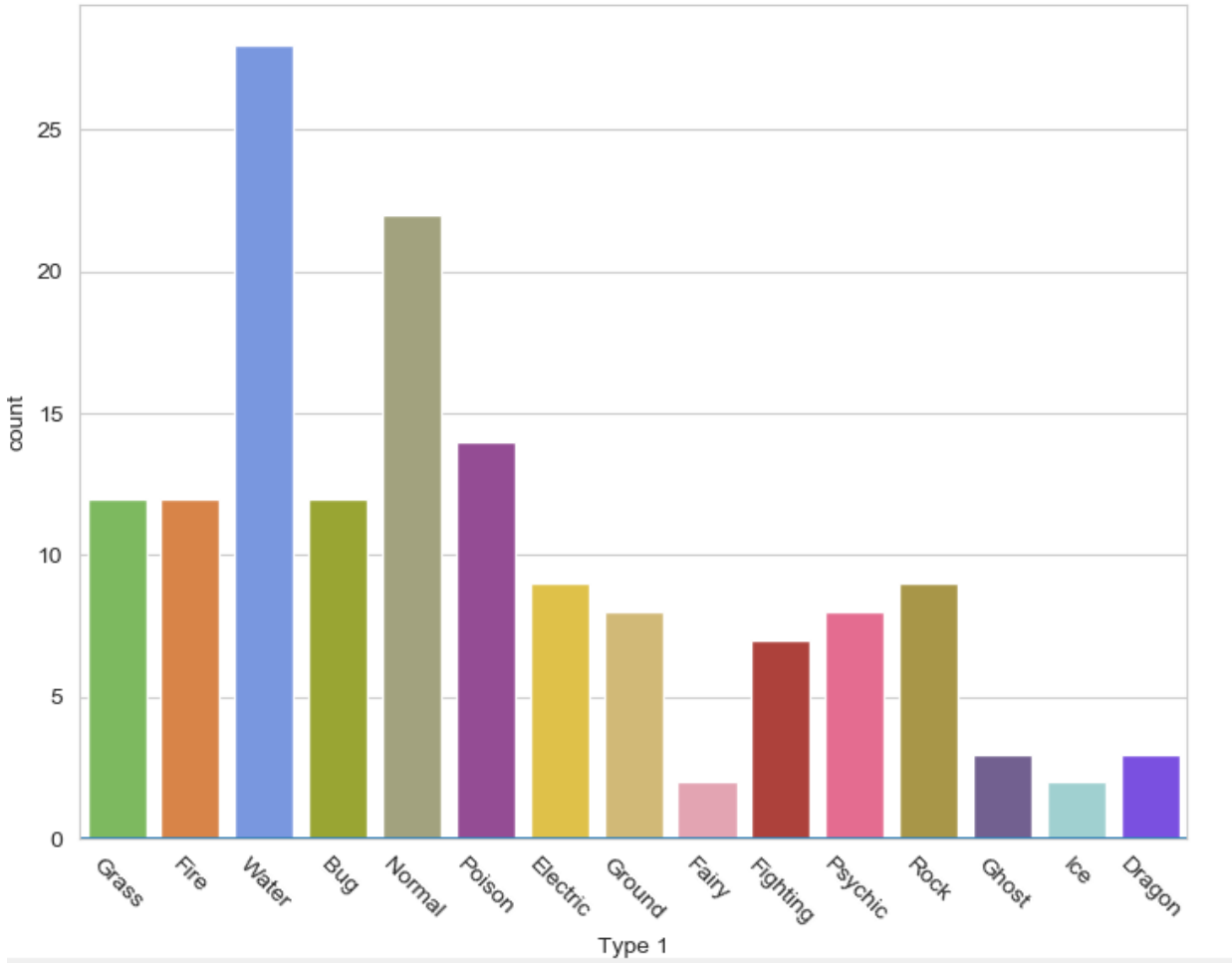


Bar plot

- Visualises the distributions of categorical variables.

```
sns.countplot(x='Type 1', data=df1,
              palette=type_colors)
plt.xticks(rotation=-45)
```

Rotates the x-ticks 45 degrees



Joint Distribution Plot

- Joint distribution plots combine information from scatter plots and histograms to give you detailed information for bi-variate distributions.

```
sns.jointplot(x='Attack',
              y='Defense',
              data=df1)
```